User-Centric Routing Based on Residents' Needs and Preferences

Ivan Mitev[1], Kaloyan Kramitov[1], and Dessislava Petrova-Antonova[1,2(✉)]

[1] GATE Institute, Sofia University "St. Kliment Ohridski", 1164 Sofia, Bulgaria
{ivan.mitev,kaloyan.karamitov,dessislava.petrova}@gate-ai.eu
[2] Faculty of Mathematics and Informatics, Sofia University "St. Kliment Ohridski", 1164 Sofia, Bulgaria

Abstract. Walkability indices are widely used to support sustainable urban planning and pedestrian routing, but most existing approaches adopt a one-size-fits-all approach that fails to capture the preferences of different subpopulations within the city. This paper proposes a user-centric walkability framework with user-specific weighting that supports personalised route choice. Based on a comprehensive literature review, the framework examines micro-scale elements of the built environment used to compute max-reward routes through the city of Sofia. To ensure the interoperability of the reviewed scoring frameworks, macro-feature weights are translated and normalised using a multi-criteria decision analysis approach based on a correspondence matrix. The results highlight a systematic mismatch between conventionally suggested routes and optimal routes for underrepresented populations. The proposed framework provides a transferable basis for more inclusive, data-driven navigation services and city planning.

Keywords: Walkability Score · User-Centric Routing · Pedestrian Comfort · Pedestrian-friendly Urban Environment

1 Introduction

Walkability, defined as the extent to which an area supports walking, has become a crucial consideration in sustainable urban planning. Cities around the globe recognise the multifaceted benefits of good walkability, including improved public health, social cohesion, lower carbon emissions and more efficient land use [1, 2]. Researchers have accordingly developed various walkability indices as decision-support and urban-planning evaluation tools. Some of these indices have been developed for general purposes, while others aim to address the walkability preferences of specific population groups, such as women, children, the elderly, tourists, or people with disabilities. Neglecting the perspectives of these groups can lead to a measurable mismatch between official walkability scores and individuals' actual walking experiences [3]. For example, studies have shown that women perceive urban spaces differently from men due to concerns about personal safety and harassment [4]. Similarly, the senior population and the elderly face age-related constraints that are not captured by typical indices, such as poor lighting, steep

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2027
O. Gervasi et al. (Eds.): ICCSA 2026 Workshops, LNCS 16765, pp. 436–454, 2027.
https://doi.org/10.1007/978-3-032-30536-7_28

hills, or poorly paved roads, which can be minor nuisances for younger people. When walkability indices ignore these factors, they overestimate the walking friendliness for the different population

groups affected by them. The same issue persists for people with mobility impairments because they constitute a small percentage of the population, and walkability indices are often not tailored to their needs. This overlooks crucial elements that might discourage, or even physically prevent, people in wheelchairs from taking a certain path. Features such as continuous curb ramps, smooth ground surfaces and unobstructed sidewalks are crucial for wheelchair users [5]. Children also have unique needs, since they value wide sidewalks on which they can safely run, safe crossings and slow traffic speeds [6]. Tourists also represent a special category of pedestrians, often neglected in walkability research. Past research shows that, in many ways, tourist walkability overlaps with that of the general population [7]. However, places a much higher importance on cultural and historical monuments, ambient areas with traditional architecture, and the availability of stores and restaurants.

Recent research on composite walkability indices has demonstrated robust approaches to capturing the multidimensional nature of walkable environments. For example, the study by Appolloni et al. developed a so-called walking suitability index of the territory (T-WSI), which assesses neighbourhood-scale walkability through 12 micro-indicators spanning the macro-categories of practicability, safety, urbanity, and appeal [8]. However, this method relies on street-level audits and is better suited to area-wide evaluation than to single-path analysis. Similarly, Ruiz-Padillo et al. proposed a weighted index utilising a multi-criteria Fuzzy Analytic Hierarchy Process (Fuzzy AHP) to derive meaningful scores for street segments, even when they do not fully fall within a single predefined category [9]. Their case study of Porto Alegre, Brazil, demonstrated the universal importance of factors such as public security, traffic safety, and pavement quality in influencing walkability.

Beyond individual indices, recent reviews have synthesised common patterns and gaps in walkability metrics [10]. Fonseca et al. reviewed 132 studies and observed that most composite indices emphasise macro-scale attributes such as residential density, land-use mix, and intersection density. The study found that small-scale streetscape design and security features are underrepresented in conventional walkability assessments. Similarly, Akinci et al. conducted a systematic review of 146 studies, 24 on the elderly and 122 on the general population, to analyse trends in walkability scores for the two population groups [11]. Their study revealed discrepancies in the examined features between elderly people and the general population, such as mismatches in the importance placed on safety, path quality, steepness, and the abundance of greenery. Such results suggest that a one-size-fits-all index often marginalises or completely excludes underrepresented groups.

This study aims to evaluate and combine existing approaches to estimate the walkability index, thereby developing a set of metrics that account for the needs and preferences of different population groups. It also provides a means to measure the difference in routes proposed by those metrics.

The rest of the paper is structured as follows. Section 2 describes the walkability scoring methodology. Section 3 presents the results from its application, including optimal route finding for different population groups. Section 4 concludes the paper and outlines future work.

2 Walkability Scoring Methodology

The complete study workflow is shown in Fig. 1. Its subsequent steps are explained in detail in the following sections.

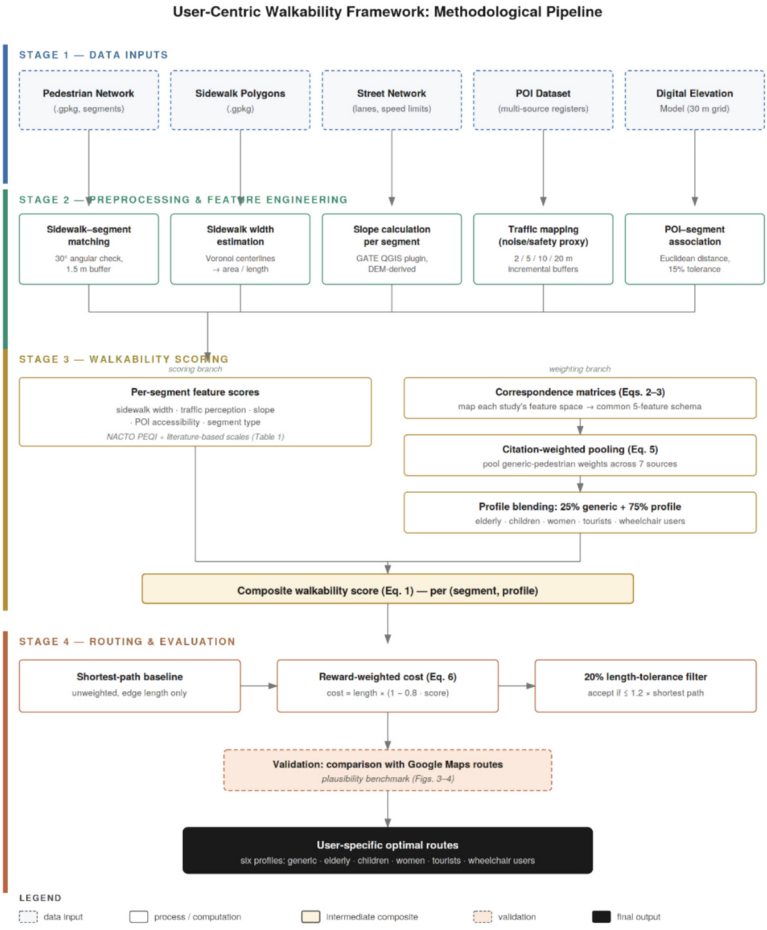


Fig. 1. Methodology Workflow

2.1 Study Area and Datasets

The framework is developed and evaluated on the municipality of Sofia's street network, the capital and largest urban centre of Bulgaria, with a population of approximately 1.2 million. Sofia lies in the Sofia Valley and is bounded to the south by the Vitosha massif, which produces significant topological variation (Fig. 6). Street gradients vary widely, even within central districts, enabling slope to be used as a discriminative feature in the proposed methodology. Additionally, Sofia is a useful test location because of its heterogeneous urban layout. The historic core, organised around pre-socialist boulevards and squares, hosts most of the city's heritage sites, museums, cafes, restaurants and stores. These features result in a tourist profile that is substantially distinct from the generic pedestrian. Surrounding the core are socialist-era residential districts marked by panel-block housing with variable sidewalk quality and widths. Beyond the ring road, post-1990 urban development has produced car-centric suburbs with weaker pedestrian infrastructure [12]. This range of built environment features spans the full range of conditions the framework is designed to differentiate and supports meaningful comparisons across user groups.

The pedestrian network is stored as a vector layer and provided in .gpkg format. Each segment of the network represents a walkable path with several attributes such as name, type and length in meters. Sidewalks, streets, parking areas, bike lanes and parks are represented as polygons in .gpkg format. They are characterised by attributes like area and perimeter. A Points of Interest (POIs) dataset is collected from multiple sources, including open data platforms, national, regional, and local registers. It includes urban facilities that citizens frequently use, grouped by primary function and further divided into subgroups based on specific functions, with consideration of their significance to citizens' well-being [1]. The street network is stored as a vector layer in .gpkg format. The network segments are characterised by attributes such as vehicle speed limits and the number of lanes.

2.2 Data Preprocessing

Before evaluating the quality of pedestrian network segments and computing composite walkability scores, several preprocessing steps are taken. This included various data enrichment procedures to add attributes via spatial indexing, including calculating sidewalk widths and the slopes of street segments.

The pedestrian network segments and sidewalk polygons do not originate from the same dataset, and therefore, a matching procedure is developed. First, the network segments representing sidewalks are split at bends with angles greater than 30°. This ensures that no segments fall within multiple streets [13]. After that, a spatial buffer is added to the polygons because, in many cases, the segments do not overlap them directly. While Brezina et al. use a 5-m buffer to associate street centerlines with sidewalk polygons, this study uses a 1.5-m buffer to associate pedestrian network sidewalk segments with sidewalk polygons. This decision is based on the fact that along a single street, there are often two sidewalk polygons and two sidewalk segments, representing the sidewalks on the two opposing banks. After buffering, a final check is conducted to examine if the angular alignment of the polygon and segment differs by more than 30°. If this is true,

the segment is assumed to be a "rogue" one, not representing the same sidewalk as the polygon [13].

The sidewalk polygons are enriched with a width attribute, derived from the polygon's area and length. The area is an inherent polygon attribute, but the length requires additional calculation. Voronoi tessellations are used to draw close-to-optimal centerlines [14]. After that, the average width of each polygon is calculated using the standard formula for a rectangle [13]. Considering that a street's sidewalk is represented by multiple polygons, and therefore multiple measurements are taken for each street, this calculation provides an estimation of where sidewalks of insufficient widths might be encountered. The slope of pedestrian network segments is obtained using the GATE QGIS plugin, which utilises segment-wise slope calculation with a Digital Elevation Model (DEM). The DEM contains height measurements taken at 30-m intervals, making calculations more precise for long street/network segments.

Pedestrian network segments are analysed with respect to traffic noise, a key source of pedestrian discomfort. An algorithm is developed to associate pedestrian network segments with corresponding street segments. Traffic-related discomfort is estimated using the number of traffic lanes and the maximum permitted vehicle speed. For each pedestrian segment, the algorithm computes its directional angle (alignment) and generates a spatial buffer. Street segments whose angular alignment differs by no more than 30° from that of the pedestrian segment are considered candidates and are mapped accordingly. If no matching street segment is identified, the buffer distance is incrementally expanded. Buffer distances of 2, 5, 10, and 20 m are applied, as empirical inspection indicates that larger buffers frequently result in incorrect mappings to streets separated by vegetation or located on the opposite side of buildings. Such barriers substantially reduce perceived or actual noise levels [15, 16].

An important criterion for evaluating the quality of a pedestrian network is its accessibility to various POIs. To determine which POIs are accessible from which network segments, an algorithm is developed, iterating through all POIs and calculating the Euclidean distance from each POI to the surrounding lines [17]. The ten closest segments are identified, and the POI is marked as accessible from the closest segment as well as from any other segment that is no more than 15% farther than the top candidate. This is useful for mapping POIs in dense parts of the network, such as fountains, monuments, and statues in public parks and squares, where a POI is effectively accessible from multiple pedestrian segments. At the same time, this approach is precise enough to avoid associating stores, restaurants, cafés, pharmacies, schools, and other POIs located in a building with pedestrian network segments on the opposite side of the building.

2.3 Walkability Scoring

To find the most comfortable route from point A to B, a max-reward path-finding algorithm is developed with a different reward function value for each population group. The first step is to assign reward values to each segment of the pedestrian network. The reward function is calculated according to Eq. 1 as follows:

$$\sum_{i=1}^{n} w_i \times s_i(e) \tag{1}$$

where w is the weight of this scoring category, and s is the quality score of the feature for the corresponding segment.

Table 1 compares different methods for scoring the quality of the micro-attributes of street segments. The "Score" column includes the scoring approaches used in the studies examined in this paper's literature review. The "Pedestrian Quality Index" column contains the relevant scoring method used by the National Association of City Transportation Officials (NACTO) [18].

Sidewalk Width. Sidewalk width scores are calculated from the sidewalk's width attribute. After examining two width-scoring approaches [1, 19]. The approach proposed by the San Francisco Department of Public Health was chosen for its greater relevance and better data separation. While Shaaban's methodology [19] is easier to use and has been developed for sidewalks measured in metric distances, the metric does not account for the specifics of Doha's cityscape, which differs from Sofia's pedestrian infrastructure and walking habits, as well as those of San Francisco. Moreover, NACTO's scoring system [18] led to a more meaningful distinction between sidewalks, as the mean sidewalk width in Sofia was approximately 2.5 m. Sidewalk width scores are only assigned to pedestrian network segments of the sidewalk subtype and are considered only when available. This means that when choosing between two edges of type "sidewalk", the algorithm selects the one with the larger width. Such a choice is most useful in urban neighbourhoods, where selecting adjacent streets or sidewalks does not drastically affect travel time but can substantially affect perceived walking comfort.

Traffic Perception. This score is a composite evaluation of the noise and safety effects of heavy traffic in the built environment. Traffic volume, the number of lanes and speed limits all correlate with the perceived pedestrian safety of walking areas [10]. These features also contribute to noise pollution, which reduces the appeal of adjacent pedestrian areas [16]. Here, NACTO's scoring system is chosen again, as it splits segment scoring into two independent parts: one for the number of lanes and another for the speed limit. In the case of the provided data, this proves useful because there are different types of streets and boulevards that share one of these two features but never both. This methodology enables greater granularity in the types of streets examined. Only pedestrian segments within a 20-m Euclidean distance of a traffic street are evaluated. Segments beyond that receive the maximum possible score for traffic perception, as in most cases, there is either a building or another physical obstruction between the pedestrian segment and the street [16].

Slope. As NACTO [18] does not have a comprehensive steepness scoring system, the slope is evaluated based on current literature, which suggests that an incline of 8% is critical for most pedestrians [8]. Although this metric has long been debated, as hilly areas often have many streets with higher inclines, in this study, it is assumed that pedestrians are generally willing to take a detour when the incline exceeds 8%. On the other hand, any slope below 2% is still considered usable, even by physically challenged users. The rest of the range (2–5% and 5–8%) is split to ensure data granularity.

POI Accessibility. POI accessibility measures how close the street segment is to mobility infrastructure, green infrastructure, schools and educational facilities, child social infrastructure, health facilities, sports infrastructure, cultural infrastructure and retail

Table 1. Scoring metrics.

Category	Score	Pedestrian Quality Index
Width	0–1 m = 0.1 1–1.5 m = 0.3 1.5–2.5 m = 0.6 >2.5 m = 1 [19]	0 = 4 0–1.52 m = 7 1.52–2.41 m = 13 2.41–3.63 m = 19 More than 3.63 m = 22
Noise disturbance / Traffic perception	No adjacent street = 1 Adjacent street with 1 lane = 0.7 Adjacent street with two lanes and speed limit = < 50 = 0.5 Adjacent street with two lanes and speed limit >50 && = < 80 = 0.2 Adjacent street with more than two lanes or speed limit >80 = 0 [10].	Lanes: 0 = 24 1 = 22 2 = 19 3 = 9 4+ = 4 Speed Limit: < 32.2 km/h = 27 Not posted (0) = 22 32.2–40.2 km/h = 22 41.8–56.3 km/h = 12 > = 56.3 km/h = 2
Slope	0–2% = 1 2–5% = 0.70 5–8% = 0.35 >8% = 0 [8]	
POI accessibility	0–1, [1]	Retail Use: 0 = 9 1–2 = 11 3+ = 19
Type	Sidewalk = 1 Crossing with a traffic light = 0.7 Zebra crossing = 0.6 Parking = 0.2 Unregulated crossing = 0 Paved parkway = 0.9 Unpaved parkway = 0.8 Parkway = 0.8 Underpass = 0.3 Overpass = 0.3 Road surface (all other types) = 0	

and services. This metric builds on previous work using the same POI dataset [1]. However, here, each POI is only associated with the street segments it is accessible from, rather than having an area of effect that encompasses all segments surrounding it. The scoring of this feature follows NACTO's "Retail Use" score [18]where more than 3 accessible POIs indicate that the segment is well connected. The reason for capping the score at three POIs is that pedestrian segments are relatively short (often only one

city block). Moreover, not capping the score favoured shopping malls and other retail clusters, unlike the pathfinding algorithm.

Type. This score is designed to place greater emphasis on more pedestrian-friendly aspects of the network. Since this feature is highly dataset-dependent and the segment types are not standardised, a custom scoring methodology is used. Specifically, traffic lights and other regulated crossings are given a higher score than unregulated crossings. Likewise, sidewalks are given a slightly higher score than parkways, as walking through a park should be discouraged under certain conditions, such as at night or when the unpaved areas are wet. Finally, underpasses and overpasses receive a low score, as pedestrians often view them as natural barriers and would rather take a path around them than use them [20]. Additionally, navigating public parking lots or walking on streets used by cars is highly discouraged.

2.4 Weights

This section describes the procedure and justification for selecting the specific weights. It begins with a description of the default pedestrian type and its weights, then proceeds to details on how the weights are adjusted to suit the other population groups.

The weights for each population group are calculated based on current literature. Since different studies have used varying features to assess walkability, these features have to be mapped to the available data. This is why an approach from Multi-Criteria Decision Analysis, known as a correspondence matrix (also called a concordance or crosswalk), is used. Conceptually, this matrix specifies the fraction of each source feature to be reassigned to each target feature, allowing one-to-many and many-to-one mappings while maintaining overall importance. When the matrix is applied to a study's weight vector, its "weight mass" is redistributed from the study's native feature-space into the common schema, yielding a directly comparable set of weights. When multiple papers are used, papers are reweighed by the count of their citations. An example application of the correspondence matrix algorithm is given here. Note that in this study, all cells in the mapping matrix have a value of either 0 or 1 to avoid distributing weights in an uninformed or random way:

1. Collect all of the scoring weights used in the paper in a 1xN matrix.

$w^{(p)}$: [Pedestrian infrastructure = 0.2, Maximum speed = 0.1, Crossing availability = 0.25, Noise level = 0.05, Gradient = 0.3, Greenness = 0.1]

2. Create a mapping matrix M where each row corresponds to one of our scoring features and each column to one of the features used in the paper.

$$M^{(p)} \in R^{n \times K_p} \tag{2}$$

where M is an $m \times p$ matrix, p is the number of features in the examined paper, n is the number of features (5 in the current study), K_p is the length of the list of features (weights) in the examined paper.

Table 2 presents an example matrix with the values mapped.

Table 2. Sample correspondence matrix.

	Pedestrian infrastructure	Maximum speed	Crossing availability	Noise level	Gradient	Greenness
Sidewalk width	0.8	0	0	0	0	0
Traffic perception	0	1	0	0.8	0	0
Slope	0	0	0	0	1	0
POI accessibility	0	0	0	0.1	0	0.1
Type	0.2	0	1	0.1	0	0.2

3. Translate the matrix into features by multiplying the matrix by the matrix of the paper's scoring weights.

$$\hat{W}^{(p)} = M^{(p)} \times w^{(p)} = [0.160, 0.140, 0.300, 0.015, 0.315] \tag{3}$$

4. Renormalise the weights so that they sum to 1.

$$W = \frac{\hat{W}^{(p)}}{\sum \hat{W}^{(p)}} = [0.172043, 0.150538, 0.322581, 0.016129, 0.338710] \tag{4}$$

5. Combine the scores of all papers. Pool all of the scores and weight them differently based on the number of citations each paper has received.

$$W_{pool} = \frac{\sum_{p=1}^{p} \alpha_p W^{(p)}}{\sum_{p=1}^{p} \alpha_p} \tag{5}$$

6. For each user type, reweigh the scoring weights with the generic pedestrian weights contributing 25% and the weights derived from the user type paper contributing 75% of the final weight.

Generic Pedestrian. This is a primary pedestrian group whose weights are calculated based on the literature [8–11]. All subsequent weight profiles utilise the generic pedestrian's weights, reweighed according to their specific requirements. The employed studies propose weighing based on surveys of pedestrians, surveys of experts in the field, direct data collection from phone walking habits, and a literature review of previous studies on the topic. Therefore, when computing the composite weights, the studies are reweighted by their number of citations.

Elderly. The weights for the elderly population are based on the study by Ye [21], with a contribution of 75% compared to 25% from the generic pedestrian weights. The elderly's walkability perception centres on functional accessibility, comfort, and safety

from crime, rather than traffic safety. High-density, mixed-use areas enhance perceived walkability, while well-maintained, properly paved paths ensure walking safety. After translating the weights via a correspondence matrix, metrics such as sidewalk width and traffic perception become less important, while slope, the number of accessible POIs, and street type become more important. The employed metrics are the "Land use mix – access" mapped to POI Accessibility, and "Street connectivity", mapped to Type.

Children. The weights for the children population are based on the study by Zuo [6]. The employed metrics from the study are the "Effective street width" mapped to Sidewalk with, "Interfacial diversity" mapped to POI Accessibility, "Street flatness" mapped to Slope, "Green looking ratio" mapped to Type, and "Sound Decibels" mapped to Traffic perception. According to the survey, the children prioritise flat, clean and sufficiently wide streets and therefore would prefer paved walking paths. High-traffic streets also seem to be unpopular among children due to noise, vehicle encroachment, and deficiencies such as potholes and obstructions. Quantified, these findings indicate a rise in the importance of slope, POI Accessibility, and Type weights, and a decrease in Traffic perception.

Women. The weights for the female population are based on the study by Golan et al. [4]. Women rank crime, homelessness and physical safety as the most important factors when selecting a walking path. Moreover, they described avoiding streets with encampments, large groups of men or poor sanitation. Secondary factors included vehicular traffic, parks and open spaces and types of nearby businesses. Streets with many amenities were ranked high, but only when they were perceived as safe and maintained. The negative correlation between a general, ungendered Walk Score and the proposed Walkability Index for Women is examined. Often, areas with a high Walk Score were the least desirable for women due to concerns about safety or cleanliness. The employed metrics are the "Sidewalk Quality" mapped to Sidewalk width, and "Presence of Parks", mapped to Type, "Vehicular Traffic Volume", mapped to Traffic perception, "Types of Businesses", mapped to POI accessibility, and "Slope", mapped to Slope.

Tourists. The weights for the tourists are based on the study by Hassanshahi et al. [22]. Tourists favour streets that are connected to cultural and heritage sites, mixed-use tourism-compatible POIs such as cafes, shops, and restaurants, and streets with high security metrics. Additionally, tourists favour highly connected, integrated streets that facilitate natural pedestrian movement. It is suggested that urban planners should prioritise heritage visibility and route connectivity, enhance safety and ensure public transit access while maintaining comforts such as access to food and beverages. The employed metrics from the study are the "Imageability and heritage assets" mapped to POI accessibility, and "Land use and activity", mapped to Type, "Traffic safety", mapped to Traffic perception, "Accessibility", mapped to POI accessibility, and **"**Comfort and convenience**"**, mapped to Sidewalk width.

Disabled People. The wheelchair-user weights are based on the study by Jehle et al. [3]. The study finds that barrier-free sidewalks and sidewalk width are the most important features for wheelchair users, as they enable them to traverse a given sidewalk. Additionally, the discomfort caused by sloped streets scales faster for wheelchair users, and their tolerance for slopes is lower. Wheelchair users also prefer smooth, paved streets

and parkways, and unpaved streets affect them more than pedestrians. Therefore, traffic perception and POI density are less important to them. The employed metrics from the study are the "Sidewalk width" mapped to Sidewalk width, and "Slope", mapped to Slope, "Number of car lanes", mapped to Traffic perception, "Max speed", mapped to Traffic perception, "Safe street crossings", mapped to Type, "Underpasses", mapped to Type, and "Number of POIs", mapped to POI accessibility.

Table 3 summarises the weight for the different population groups.

Table 3. Metric weights.

	Generic pedestrian	Elderly	Children	Women	Tourists	Wheelchair users
Sidewalk width	0.136395	0.175347	0.205741	0.127074	0.143616	0.302828
Traffic perception	0.279145	0.225661	0.191677	0.249538	0.199838	0.130861
Slope	0.125414	0.159484	0.156975	0.188378	0.031353	0.182819
POI accessibility	0.220057	0.221011	0.206756	0.203775	0.405080	0.094102
Type	0.238988	0.218496	0.238851	0.231235	0.220112	0.289389

2.5 Routing

Computing the paths includes calculation of the fastest path and all lowest-cost paths with a cost reduction of 0.8, using the following equation:

$$\text{cost}_{\text{edge}} = \text{length}_{\text{edge}} \times \left(1 - \text{cost}_{\textit{reduction factor}} \times \text{score}_{\text{walkability}}\right) \tag{6}$$

The candidate for the lowest-cost path was accepted only if its total length was within 20% of the shortest path's length. Since walkability scores are precomputed offline, the routing query reduces to a shortest-path search, making it computationally feasible to integrate with navigation services.

3 Results

3.1 Walkability Scores and Coefficient of Variation

Examining walkability scores across all population groups, it is clear that walkable areas of the city are located within urban neighbourhoods. Pedestrian network segments outside the ring road, where most roads are used only by cars or have poorly maintained sidewalks, score significantly lower than those within the city.

Fig. 2 summarises the city-wide segment scores for each of the six user profiles. The highest scores are concentrated in the inner-city neighbourhoods within Sofia's ring

road. In contrast, remote neighbourhoods with more car-centric design and walking paths along busy roads and heavy-traffic boulevards score lower across all user groups. This is explained by infrastructure quality, wide sidewalks, alleys within parks, regulated sidewalks, and a higher POI concentration. The framework's POI, traffic, and type features are the main drivers of this difference between inner-city and outer-city scores.

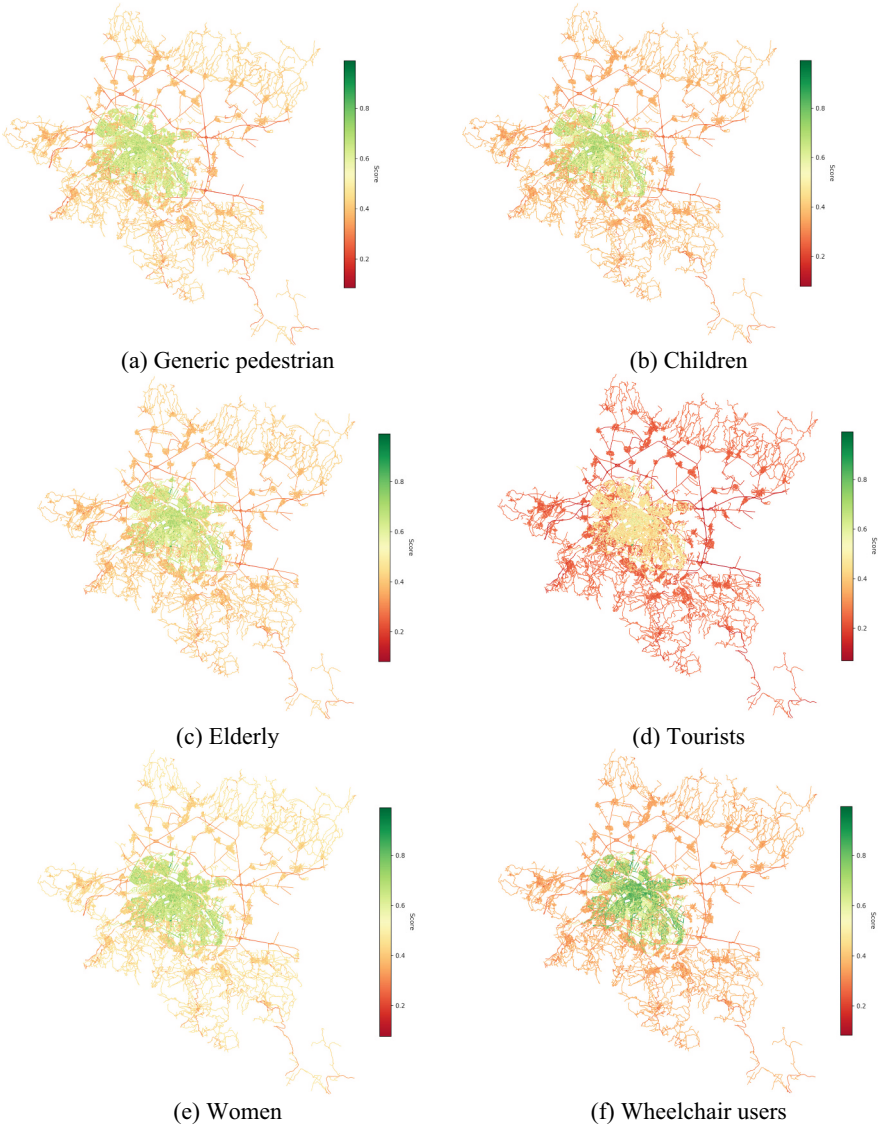
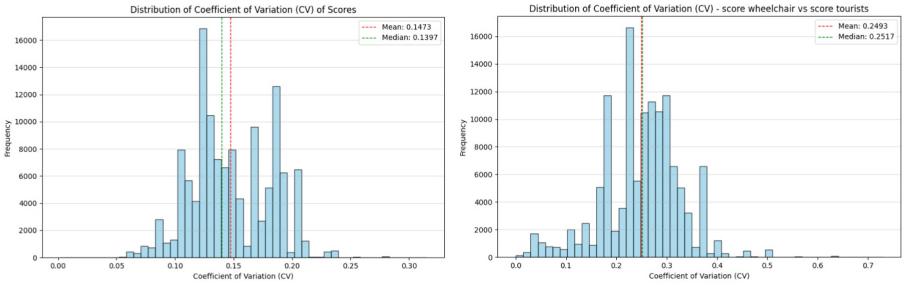


Fig. 2. Walkability scores of the generic pedestrian group (a), the children group (b), the elderly group (c), the tourist group (d), the woman group (e) and the wheelchair user group (f).

The generic pedestrian, children, elderly, and women categories produce similar patterns (Fig. 4a-c, Fig. 2e). This indicates that, despite some weights differing, the shared or similar weights (POIs, traffic, type) are significant enough to drive the results in the same direction. The difference in scores becomes clearer with the more specialised profiles. The wheelchair user profile (Fig. 2f) shows a more pronounced difference between its highest- and lowest-scoring paths. This profile assigns an extremely high score to a selected set of pedestrian segments within the city centre, with apparently high scores in the sidewalk width and segment type categories. Another outlier is the tourist profile (Fig. 2d), which focuses mainly on POI accessibility. As a result, it assigns a lower overall score to the city network. However, more informative than the overall score is the difference between different areas within the city. It is apparent that this type of user prefers inner-city areas with nearby POIs, such as historical sites, cultural venues, restaurants, and entertainment venues.

Analysing the Coefficient of Variation (CV) scores reveals that there is generally little variation between different user groups (see Fig. 3). This is to be expected, as most population groups consider the same attributes of the pedestrian network to be the most important. However, the difference between groups with little in common increases sharply. For example, the CV between wheelchair users and tourists is nearly double that of all other indices. This supports the findings of the literature review and suggests that user groups with divergent requirements may assign different scores to the same edges of the network.



(a) All scores (b) Generic pedestrian and wheelchair user

Fig. 3. Coefficient of Variation between the scores of all population groups (a) and between generic pedestrian and wheelchair user groups.

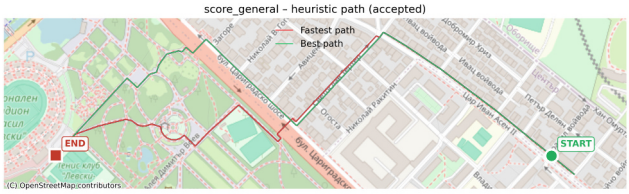
3.2 Optimal Route Finding

To evaluate the path-finding capabilities of the proposed methodology, a routing algorithm was developed. The paths were evaluated against a commonly used pedestrian navigation application. After the shortest paths were calculated, they were visualised alongside the shortest path. Also, a visualisation of the best paths for all user groups was created to examine how they differ. The results aligned with those from the previous section. Most subpopulations followed paths very similar to the best option. However, the groups with more specific requirements, such as tourists, wheelchair users, and, to a lesser extent, women, sometimes preferred different paths than the other groups (see Fig. 5), which aligns with the CV scores. Additionally, there was a high overlap between the paths suggested by Google Maps (see Fig. 4) and the fastest paths found by the path-finding algorithm (see Fig. 5). Moreover, the alternative paths suggested by Google Maps often overlapped with one or more user groups' preferences.



Fig. 4. Routing paths suggested by Google Maps.

(e) All user-groups compared



(a) Generic pedestrian



(b) Tourists



(c) Women



(d) Wheelchair users



(e) All user-groups compared

Fig. 5. Optimal routing paths, calculated for each population group.

4 Discussion

The study was motivated by a recurrent observation in the current literature. Composite indices designed for the general population tend to underrepresent groups whose needs diverge from the average. The results empirically address this concern, clarify where such divergences occur, and measure them on a shared network.

4.1 Findings in Relation to Prior Work

The walkability score maps for the different user profiles (Fig. 2a-c, e) show broadly similar spatial patterns. This is consistent with the central finding of Fonseca et al. [10], indicating that macro attributes like residential density, land-use mix, etc., dominate composite indices. In the proposed framework, these attributes are presented as weights, including POI accessibility, traffic perception, and segment type. Although the weights of these features differ across user groups, they are sufficient to roughly align the scores within each user group across different areas of the city.

The point where the framework departs from a one-size-fits-all index is the divergence between profiles with distinct infrastructural requirements. This is best exemplified by the CV metric, which is nearly double when measuring wheelchair users versus the general population compared to the average value between all user groups (Fig. 3). This, in addition to the routing experiments (Fig. 5), confirms that specific user profiles often select paths different from the general population. This pattern aligns with the review of Akinci et al. [11], who found measurable discrepancies between walkability operationalisations that focus on the elderly and those that target the general population. Their paper also concludes that a one-size-fits-all framework marginalises groups with special needs. The present framework extends this beyond the elderly-versus-general comparison, suggesting that marginalisation is not uniform but is largest for tourists [22] and wheelchair users [3], and smaller for women, the elderly, and children.

4.2 Methodological Contribution

Among the multi-criteria approaches reviewed, the closest methodological precedent is Ruiz-Padillo et al. [9], who apply a Fuzzy Analytic Hierarchy Process to derive walkability weights for the Porto Alegre region. Their approach is similar to that of Campisi et al. [20]. It derives weights from a single expert or stakeholder and applies them to a specific area. The correspondence matrix introduced differs from the approaches they used. It pools weights across a set of studies, each with its own distinct feature schema, by mapping every study's feature space onto a shared five-feature representation. The practical advantages come in the form of transferability, as the framework enables easier addition of new user groups or reevaluating current groups, as these actions require only the mapping of a relevant study.

4.3 Limitations

Two limitations should be made explicit. First, POI accessibility is operationalised through Euclidean distance with a 15% tolerance threshold for segment association. While this is a viable simplification of the association task as POIs are accessed from the nearest network segment, it does not capture distance-weighted accessibility throughout the graph. Second, validation is currently limited only to a benchmark with existing navigation applications, which does not directly establish user preferences.

5 Conclusion

This paper presents a user-centric framework for assessing walkability and pedestrian route planning, which accounts for the varying preferences of different population groups. Using Sofia's pedestrian network and supporting datasets, the study operationalises five metrics on the segment level (sidewalk width, traffic perception, slope, POI accessibility and segment type). The results indicate that even with common, readily available data, walkability patterns can show meaningful differences. Although walkability scores remain broadly consistent across user groups, meaningful mismatches are observed between populations with divergent requirements, namely tourists and wheelchair users. Routing experiments show that user-specific scoring can yield paths different from those generated by standard navigation tools. This illustrates the need for user-specific routing and evaluation options.

Future work should (i) implement a more sophisticated method for POI to network segment mapping (ii) further validate the framework through replication using data from different cities; (iii) use different underlying studies to test the scope to which the framework can be applied; (iv) incorporate additional user-groups and new micro-scale features (where possible) to increase the relevance of the suggested paths; (v) update weights using population-specific surveys to decrease the reliance on priors based only on past literature.

Acknowledgments. This research is part of the GATE project funded by the Horizon 2020 WIDESPREAD-2018-2020 TEAMING Phase 2 programme under grant agreement no. 857155 and the programme "Research, Innovation and Digitalization for Smart Transformation" 2021-2027 (PRIDST) under grant agreement no. BG16RFPR002-1.014-0010-C01, the deployEMDS project, funded by the Digital Europe Programme DIGITAL-2022-CLOUD-AI-03 under grant agreement no. 101123520 and the CU project, funded by the Digital Europe Programme DIGITAL-2023-CLOUD-AI-04 under grant agreement no. 101168005.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Petrova-Antonova, D., Murgante, B., Malinov, S., Nikolova, S., Ilieva, S.: Walkability analysis of Sofia's neighborhoods powered by 15-minute city concept. Cities. **165**, 106171 (2025). https://doi.org/10.1016/j.cities.2025.106171
2. Karamitov, K., Petrova-Antonova, D.: Pedestrian accessibility assessment using spatial and network analysis: a case of Sofia City. Int. Arch. Photogramm. Rem. Sens. Spatial Inf. Sci. **XLVIII-4/W5-2022**, 53–60 (2022). https://doi.org/10.5194/isprs-archives-XLVIII-4-W5-2022-53-2022
3. Jehle, U., Larriva, M.T.B., BaghaiePoor, M., Büttner, B.: How does pedestrian accessibility vary for different people? Development of a perceived user-specific accessibility measure for walking (PAW). Transp. Res. A Policy Pract., 104203

4. Golan, Y., Wilkinson, N., Henderson, J.M., Weverka, A.: Gendered walkability: building a daytime walkability index for women. JTLU. **12** (2019). https://doi.org/10.5198/jtlu.2019.1472
5. Horn, J.: Walking as an approach to the socially-ecological transformation of inclusive urban mobility systems: An explorative case study involving disabled people in Berlin, https://hdl.handle.net/10419/299230, (2024).
6. Zuo, J., Mu, T., Xiao, T.-Y., Luo, J.-C.: Evaluation of walking comfort in Children's school travel at street scale: a case study in Tianjin (China). IJERPH. **18**, 10292 (2021). https://doi.org/10.3390/ijerph181910292
7. Leung, T.M., Miao, S., Lin, M., Hou, H., Sun, M.: Tourist walkability in traditional villages: the role of built environment, Shareability, and personal attributes. Sustainability. **17**, 5311 (2025). https://doi.org/10.3390/su17125311
8. Appolloni, L., Corazza, M.V., D'Alessandro, D.: The pleasure of walking: an innovative methodology to assess appropriate walkable performance in urban areas to support transport planning. Sustainability. **11**, 3467 (2019). https://doi.org/10.3390/su11123467
9. Ruiz-Padillo, A., Pasqual, F.M., Larranaga Uriarte, A.M., Cybis, H.B.B.: Application of multi-criteria decision analysis methods for assessing walkability: a case study in Porto Alegre, Brazil. Transp. Res. Part D: Transp. Environ. **63**, 855–871 (2018). https://doi.org/10.1016/j.trd.2018.07.016
10. Fonseca, F., et al.: Perceived walkability and respective urban determinants: insights from Bologna and Porto. Sustainability. **14**, 9089 (2022). https://doi.org/10.3390/su14159089
11. Akinci, Z.S., Delclòs-Alió, X., Vich, G., Salvo, D., Ibarluzea, J., Miralles-Guasch, C.: How different are objective operationalizations of walkability for older adults compared to the general population? Syst. Rev. BMC Geriatr. **22**, 673 (2022). https://doi.org/10.1186/s12877-022-03233-x
12. Hirt, S.: Post-socialist urban forms: notes from Sofia. Urban Geogr. **27**, 464–488 (2006). https://doi.org/10.2747/0272-3638.27.5.464
13. Brezina, T., Graser, A., Leth, U.: Geometric methods for estimating representative sidewalk widths applied to Vienna's streetscape surfaces database. J. Geogr. Syst. **19**, 157–174 (2017). https://doi.org/10.1007/s10109-017-0245-2
14. Valls, F., Clua, Á.: Modeling Barcelona sidewalks: a high resolution urban scale assessment of the geometric attributes of the walkable network. PLoS One. **18**, e0284630 (2023). https://doi.org/10.1371/journal.pone.0284630
15. Ren, X., Li, Q., Yuan, M., Shao, S.: How visible street greenery moderates traffic noise to improve acoustic comfort in pedestrian environments. Landsc. Urban Plan. **238**, 104839 (2023). https://doi.org/10.1016/j.landurbplan.2023.104839
16. Haan, C.H., Kim, Y.S.: Noise Distribution Change of the Backside Urban Blocks depending on the Plans of the Roadside Buildings. Proceedings of the ICA 2019 and EAA Euroregio : 23rd International Congress on Acoustics. integrating 4th EAA Euroregio 2019 : 9–13 September 2019, 9 Sep 201913 Sep 2019; Aachen (2019). (2019). https://doi.org/10.18154/RWTH-CONV-239003.
17. Wu, T., Zeng, Z., Qin, J., Xiang, L., Wan, Y.: An improved HMM-based approach for planning individual routes using crowd sourcing spatiotemporal data. Sensors. **20**, 6938 (2020). https://doi.org/10.3390/s20236938
18. Batteate, C., Nasser, E.: Pedestrian environmental quality index (P.E.Q.I.). San Francisco Department of Public Health, UCLA COEH (2015).
19. Shaaban, K.: Assessing sidewalk and corridor walkability in developing countries. Sustainability. **11**, 3865 (2019). https://doi.org/10.3390/su11143865

20. Campisi, T., Basbas, S., Tesoriere, G., Trouva, M., Papas, T., Mrak, I.: How to create walking friendly cities. A multi-criteria analysis of the central open market area of Rijeka. Sustainability. **12**, 9470 (2020). https://doi.org/10.3390/su12229470
21. Ye, Y.: City for all ages: elderly residents' perceptions of walkability attributes in residential areas. IOP Conf. Ser.: Earth Environ. Sci. **495**, 012058 (2020). https://doi.org/10.1088/1755-1315/495/1/012058
22. Hassanshahi, G., Soltani, A., Roosta, M., Askari, S.: Walking as soft mobility: a multi-criteria GIS-based approach for prioritizing tourist routes. Front. Architectural Res. **12**, 1080–1096 (2023). https://doi.org/10.1016/j.foar.2023.09.001